Machine Learning applications for Ortho-Positronium tagging in liquid scintillator for the PROSPECT experiment

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PROSPECT Overview

PROSPECT took data at ORNL’s High Flux Isotope Reactor from 2018-2019. It is a highly enriched uranium reactor with a compact core.

14 x 11 array of 6Li doped liquid scintillator for detecting inverse beta decay from reactor antineutrinos (6m from compact highly enriched uranium reactor core)
ML to improve analysis

- Currently use tail-fraction method for pulse shape discrimination method to discriminate particles (electron-like recoil vs nuclear recoils)
- PSD and energy can be used to separate nLi capture events quite well, but electrons, gammas, and positrons are difficult
- Positron tagging using topology, possible use of Ortho-positronium formation to improve this?

**See A. Delgado’s talk for an overview of ML activities for PROSPECT and X. Lu’s talk tomorrow at 11:06 for ML applications on single ended event reconstruction**
Positron ID through o-Ps tagging

- Can we ID a subset of positrons through positronium formation?

- If the distortion in the timing distribution induced by o-Ps is not smeared by optical effects, we can use this feature as an extra handle for particle ID (P-ID).

- Initial optical simulations indicate that we are not sensitive to a 3ns OPs lifetime

![Diagram showing positron and electron paths with timing distributions for different positronium states.](image-url)
ML techniques

- Sparse convolutional neural networks are used to identify patterns in the energy deposition of various particles for particle discrimination
- PyTorch Lightning ML framework used for quick start to scalable multithreaded / GPU friendly code
- Spconv sparse convolutional library for pytorch
- Simulated gammas, electrons, positrons between 0-9 MeV randomly distributed within the detector
Particle Classification ML Architecture

- Sparse CNN -> linear
- Minimize cross entropy loss
- Stochastic gradient descent with Nesterov momentum

11x14x300 11x14x252 12x9x158 10x7x64 4480 116 3
conv 1x1 conv 3x3 conv 3x3
Stride 1 Stride 1 Stride 1
Pad 0 Pad 0 Pad 0

Dense layers
Simulated distributions

- Gamma
- Electron
- Positron

Histograms for:
- Gamma: multiplicity vs. total
- Electron: multiplicity vs. total
- Positron: multiplicity vs. total
Best Trial Results

Best trial found after hyperparameter optimization (~ 100 trials)

Used **Optuna** optimization framework

Hyperparameters tuned:
- number of convolutional layers
- number of linear layers
- number of output feature planes
- kernel size
Accuracy Distributions
Precision vs Deposited Energy and PSD

Gamma

Electron

Positron

Gamma

Electron

Positron
Multiplicity Precision

- Multiplicity is important in the network’s ability to distinguish
- More work needed to fully understand what the network is doing
  - Analyze statistical properties of pulses and topology of event

![Graphs showing precision vs. multiplicity for Gamma, Electron, and Positron](image-url)
Conclusions / Future work

- Positrons within PROSPECT can be distinguished from gammas and electrons with up to 80% accuracy using sparse CNNs based on simulated waveform data
  - More work needs to be done to understand the physical signatures and if it is learning artifacts in the simulation
- We could not distinguish OrthoPositronium in PROSPECT based on simulation but could be a useful tag in gas based detectors or high temporal resolution detectors like TPCs
- Future work:
  - Try training on / classification of real pulse data from calibration runs
  - Incorporate sparse CNN information into classification of IBD candidates
  - Improve classification by utilizing image segmentation to identify different particles within a single event
  - Improve light simulation for more realistic simulated pulses
Thanks!
https://prospect.yale.edu/
Precision - Recall / ROC curves
Simulated distributions
Best Trial Results

Best trial found after hyperparameter optimization (~ 100 trials)

Used **Optuna** optimization framework

Varied number of convolutional layers, number of linear layers, number of output feature planes, padding, kernel size
Accuracy Distributions

accuracy distribution

accuracy

0.800

0.775

x

2
4
6
8
10
12
14

0.0
0.2
0.4
0.6
0.8

0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

multiplicity
Precision vs Deposited Energy

Gamma

Electron

Positron

Muon

Neutron

NCap6Li
Precision - Recall & ROC curves
Precision Distribution (Energy - PSD space)
Confusion Matrix at selected energies

2.0 - 3.0 MeV

3.0 - 4.0 MeV
Comparison - Waveforms vs Extracted Features

Features: 2x150 16 bit samples (uncalibrated)  
Features: Energy, total photoelectrons left and right PMT, rise time, relative start time, position along cell, PSD